**Supply-side Analysis of Residential Solar Photovoltaic Financing Products**

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2017-2018 Solar Industry Economics, Technology, and Policy Research Project

LBJ School of Public Affairs

The University of Texas at Austin

May 2018

**Abstract**

The solar photovoltaic (PV) adoption model changed significantly in the mid-2000s with the emergence of various PV financing products, such as solar leases and power purchase agreements (PPAs). These financing products improved PV access for traditionally under-served populations, especially cash-constrained customers. Previous research has focused on the demand-side drivers of PV financing trends (e.g., customer adoption of various financing products), but has not explored the decision-making of PV installers and financiers when choosing where and when to offer various products—what we term 'supply side' factors.

This project studied these supply-side factors, focusing on where and when various financing products have been offered by PV installers. Using a proprietary data set of PV financing quotes from over 2,000 installers across 24 states, the project explored how different PV financing products have emerged in different markets over time. Key findings include: different installers choose to offer different types of financing products (e.g., leases, loans, PPAs); decisions by installers to offer different types of financing products can affect customer access to PV, since some customers may not receive financing offers leaving them with cash purchase as the only option; installers offer different types of products in different geographic markets; and differences in product offers may be partially explained by differences in market maturity, where nascent markets start with cash offers as the only option before PPAs quickly ramp up and mature markets see a trend of increasing cash purchases. Installers in mature markets were more likely to offer PPAs and pre-paid financing products than installers in nascent markets, and financing trends in nascent markets appear to lag behind similar trends in mature markets. Importantly, *in the sample analyzed*, by 2016 PPAs were the only non-cash financing product available to customers in both nascent and mature PV markets. Moreover, contrary to broader supply-side PV financing trends that have moved away from PPAs in recent years, results reveal that installers in this sample increased offers of PPAs in 2016, suggesting that these installers may have a different operational strategy compared to the large vertically integrated firms not in the sample.

## Introduction

Following a period of greater than 50% annual growth rates from 2012 to 2015, the rate of residential photovoltaic (PV) installations in the United States began to slow in 2016 (Perea et al. 2017). This trend is thought to be driven partially by a change in the strategy of large vertically integrated solar firms that favors development of profitable sales channels at the expense of market expansion (Litvak 2017). As part of this strategic shift, many large national firms are moving away from offering third-party-owned (TPO) PV systems to customers and are increasing focus on sales via upfront cash purchase or loans (Litvak 2017; Perea et al. 2017). TPO products, including solar leases, power purchase agreements (PPA) and upfront financing options (UFO), played an important role in expanding the early residential PV market. After reaching a peak of 72% of the national residential solar market in 2014, TPO share dropped to 47% in Q4 2016. In California, the most concentrated and oldest state solar market in the US, TPO share dropped as low as 36% in 2016 (Litvak 2017).

Drawing from behavioral economics and diffusion of innovation theory (Rogers 1993; Stern et al. 1999), research in California and Texas has helped to explain why TPO might have been successful in expanding the early US solar market (Rai et al. 2013; Rai et al. 2016; Drury et al. 2012). In the Rogers diffusion of innovation tradition, early adopters of a new technology are characterized by relatively high risk tolerance and financial liquidity, among other social characteristics. Those with higher risk aversion and lower financial liquidity tend to adopt later. TPO has been shown to attract residential PV adopters by reducing upfront costs, reducing or eliminating risk and complexity associated with PV ownership, and re-framing financial benefits into easy-to-understand electricity bill savings (Drury et al. 2012). TPO financing options attract an information-ready but cash-poor consumer segment that would not be likely to adopt solar via upfront purchase (Rai and Sigrin 2013). In a solar adopter survey, customers rated concerns about operation and maintenance and the availability of upfront funds as important determinants of their decision to adopt via TPO (Rai et al. 2016). Altogether, these studies suggest that TPO's ability to alleviate the risks and financial burden surrounding complex and capital-intensive solar PV systems may have encouraged some consumer segments to adopt earlier than they would have in the absence of TPO. As the solar industry makes a broad shift away from TPO toward purchase options, one implication is potential customers with limited upfront funds or certain risk and information preferences may be less likely to adopt a solar PV system.

Diffusion of innovation theory suggests that as solar PV adoption moves into new markets, the consumers who are likely to adopt in the early stages of emerging markets are likely to have different characteristics and preferences than consumers adopting in established markets. A recent body of solar diffusion research has begun to explore how consumer preferences and characteristics are evolving as residential solar markets mature (Reeves et al. 2017; Sigrin et al. 2015). Describing the evolution of solar PV markets over time at the level of the individual decision maker, these studies seek to provide insight to policy makers and solar firms about how to effectively promote adoption in a variety of market maturity contexts.

This paper contributes to solar market evolution research by taking on a market and infrastructure perspective (Brown 1981) and describing changes in supply-side solar PV financing product strategy. Given that TPO was an important driver of solar PV adoption in early solar markets, variation in available financing options in new markets may lead consumer adoption to take on different patterns than in mature markets. An understanding of trends in supply-side financing product strategy could be an important step in informing policy makers about where consumers may need additional support or incentives to overcome barriers to adoption. Likewise, this research might provide insight to solar firms about potential supply-demand imbalances of financing options in various market settings. We begin to address these gaps in literature by answering two research questions:

*1: How have the residential solar PV financing products offered by solar suppliers changed over time?*

*2: Do residential solar suppliers offer different financing products in mature versus nascent markets?*

Our paper begins with a background section introducing the market and infrastructure perspective on innovation diffusion. This introduction culminates in two hypotheses concerning the research questions above. Section 3 describes the data used to test these hypotheses, highlighting a proprietary dataset of quotes provided by a solar financing firm. This dataset is suited for a supply-side analysis of financing products offered by over 2,000 installers. Section 4 summarizes analyses and results in three parts. In 4.1, we address research question 1 and explore relationships between year and financing product type from 2012 to 2016. In 4.2, we address research question 2 by introducing a method for defining the maturity of county-level solar markets and then exploring whether installers working with the solar financing firm offer variable financing products in mature versus nascent markets. 4.3 describes the results of a series of multinomial logistic regression models testing how time and market maturity predict the likelihood of non-cash financing products. Lastly, the conclusion reviews findings and provides suggestions about how future studies might build on this work.

## 2. Background

### *2.1 The Market and Infrastructure Perspective*

The market and infrastructure perspective offers a framework for understanding supply-side effects on innovation diffusion, suggesting that the processes through which innovations are made available to consumers shape diffusion patterns (Brown 1981). In this framework, diffusion agencies, e.g. solar firms, are the entities through which innovations, e.g. residential solar photovoltaic technologies, are made available to consumers through three complementary stages. In the diffusion-agency establishment stage, agencies establish geographic and temporal access points through which the innovation is made available to customers. In a second stage, diffusion agencies establish operating procedures designed to encourage adoption of the innovation, which may variably target consumers based on demographic, geographic, and social characteristics. The supply-side "infrastructure" set during these first and second stages then constrains and influences the third stage of diffusion, consumer adoption. This framework emphasizes that supplier operational strategies shape the onset of innovation diffusion and subsequent patterns of demand-side adoption.

In the second stage of this framework, an example of an operating procedure that a diffusion agency might use to encourage adoption in early markets is to sell services in lieu of products (Cusumano et al. 2015). These "substitution" services (e.g. leases or PPAs) that replace the sale of products with services can help to build demand for complex, unknown, and cost-intensive innovations. For example, in the 1950s and 1960s, IBM and Xerox attracted customers to adopt mainframe computers and paper copy machines by offering bundled leasing and maintenance services (Attewell 1992). As markets mature and successful firms make large gains in scale (Carpenter et al. 1989), the costs and uncertainty surrounding an innovation decline. Increasingly, large firms cease to offer substitution services and shift instead toward complementary services such as loans and maintenance (Cusumano et al. 2015). Less resource-intensive than substitution services, business models based on complementary services allow investment in process innovation, achievement of scale, and cost-based competition, all of which may contribute to falling costs (Cusumano et al. 2015).

Applied to the solar industry, the market and infrastructure perspective on innovation diffusion suggests that it is critical to consider supply-side patterns in solar markets in attempts to promote consumer adoption of solar technologies. The diffusion-agency establishment stage for solar PV technologies has varied considerably geographically and temporally in the United States, with the earliest markets concentrated in California and subsequent markets appearing across the country (Perea et al. 2017). This has resulted in regionally diverse markets at different stages of maturity. Installation firms' operational procedures in these diverse markets have also varied, shaped by various local, state, and federal incentive programs, and also by installation firms' unique approaches to acquiring customers and providing technical and financial services.

The rapid rise of TPO among residential solar PV consumers provides an example of the effectiveness of substitution services as an operational strategy that attracts new customers in early markets (Drury et al. 2012; Litvak 2017; Perea et al. 2017). In TPO arrangements, customers pay third-party providers (TPP) periodic lease or power purchase installments for a residential solar installation, and customers benefit by monthly electricity bill savings. The TPP, which may be a vertically integrated installation company or a financing firm that purchases services from installers, maintains ownership of the system. Notably, the growth of TPO was driven by only about 10% of installation companies (O'Shaughnessy 2018). TPPs of residential solar systems have tended to be high-volume companies that are able to aggregate large numbers of PV installations and so monetize available tax incentives (MIT 2015). In 2016, firms that installed 1,000 or more solar systems per year accounted for 32% of customer-owned systems and 82% of TPO systems (O'Shaughnessy 2018). Now that PV system prices have fallen but customer acquisition costs remain high, most of these large-scale firms are moving away from substitution services toward a customer ownership model (Perea et al. 2017; Litvak 2017). To date, there is still a question about the degree to which smaller firms that offer TPO services are also moving toward a direct customer ownership model.

### *2.2 Hypotheses*

*H1:* In our analysis of a database of residential solar PV quotes, we expect that supply-side financing product trends will align with broader national trends. Specifically, we expect to see a rise of TPO offers through 2015 and then a decline of TPO offers in 2016.

*H2:* We expect that as solar suppliers reduce TPO financing in mature markets, they may continue to offer TPO financing options in nascent markets in an attempt to attract new customers.

## 3. Data

We use data from three sources in this analysis. The primary data source is a set of quotes offered by a large private firm that provides solar financing in 24 states. This dataset includes all quotes *offered* by the firm, creating an opportunity for a supply-side analysis of financing product offers across multiple markets. Importantly, these data provide insight about only this firm's operations and may not be representative of the broader solar industry. Additionally, we use Lawrence Berkeley National Laboratory's Tracking the Sun (TTS) series (Barbose and Darghouth 2016) and the U.S. Census Bureau's Annual Estimates of Housing Units for the United States, Regions, Divisions, States, and Counties: April 1, 2011 to July 1, 2016.

The financier dataset includes 778,712 quotes made to potential solar PV customers in 24 states between 2012 and 2016. The financier provides financing services that non-vertically integrated solar installation companies are not able to offer to customers. 2,361 installation companies are represented in the dataset. The relationships between the financing firm, installers, and residential solar PV customers are described in Figure 1. Typically the first contact occurs between the installer and the customer. When a customer requests financing that the installer is not able to provide, or when the installer seeks to offer financing services as a way to increase customer acquisition, the installer contacts the financing firm. The financing firm operates a software platform on which installers recommend quote specifications, including price, system components, and financing model. The financier then provides these quotes to the customer, with each quote having a financing product type of cash offer, lease, PPA, loan, UFO, or UFO/loan hybrid.

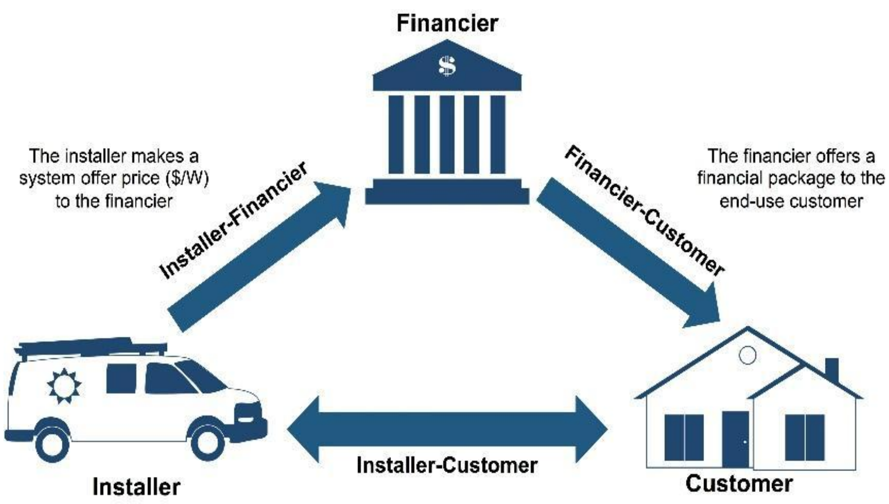


*Figure 1: Schematic of the interactions between the solar finance company that provided the data used in analysis, partnering installation companies, and customers. Installers use an online platform to suggest system offers, each with a certain financing product type, to the financier. The financier then provides offers to the end-use customer. Figure provided by O'Shaughnessy.*

Data in TTS are sourced from state agencies, utilities, and other organizations that administer solar incentive programs or interconnections. The complete TTS series includes about two thirds of all U.S. PV installations from 2000 until 2016. The TTS dataset used in this analysis includes 938,955 solar PV installations sized 15 kW or smaller for which zip code, county, and installer information are documented[1]. About 8,700 installation companies are represented. TTS reflects the rapid growth of the solar industry, including only 86 installations in 2000 and 198,826 installations in 2016.

Lastly, we use the U.S. Census Bureau's Annual Estimates of Housing Units for the United States, Regions, Divisions, States, and Counties: April 1, 2011 to July 1, 2016 dataset, which provides July 1 county-level housing estimates each year from 2011 to 2016.

## 4. Analyses and Results

### *4.1 Financing Product Type and Time*

To address our first research question and *H1*, we used the financier dataset to explore trends in the financing products offered by installation companies working with the financing firm from 2012 to 2016. To prepare the data, we excluded quotes for systems larger than 15 kW, which are assumed not to be for residential customers. UFO/loan hybrid quotes were removed from the dataset due to a low prevalence of only 21 instances. The resulting dataset includes 726,755 quotes, each of which has a financing product type of cash, lease, loan, PPA, or UFO (Table 1). From 2012 to 2015, cash offers were the leading financing type offered. Over time, PPAs grew in prevalence so that in 2016, PPA financing was more commonly quoted than cash offers. Lease and UFO offers declined from 2012 to 2016, and loans were consistently the least-prevalent financing type. A Pearson's chi-squared test reveals a significant relationship between year and

[1] The TTS dataset used in this analysis has been through two prior cleaning processes, which are described in O'Shaughnessy, 2018

financing product type ($\chi^2$ = 89,078, df = 16, p-value < 2.2e-16), suggesting that year should be used as an independent variable in further regression analysis.

*Table 1: Financing product types for 726,755 residential solar PV quotes made by the financing firm from 2012 to 2016. These data provide evidence contrary to H1 and reveal an increase in PPA bidding behavior by the firm in 2016. UFO and lease quotes appear to become less prevalent over time, while cash offers remain the most prevalent financing type until PPA's peak in 2016.*

| Financing Product Type and Time | | | | | |
|---|---|---|---|---|---|
| | 2012 | 2013 | 2014 | 2015 | 2016 |
| Cash | 42,156 (40%) | 74,328 (41%) | 79,951 (48%) | 70,133 (50%) | 53,594 (41%) |
| Lease | 23,547 (22%) | 2,382 (1%) | 8380 (5%) | 11,316 (8%) | 5,756 (4%) |
| Loan | 2,435 (2%) | 4,131 (2%) | 4,431 (3%) | 863 (1%) | 191 (0%) |
| PPA | 23,422 (22%) | 72,342 (40%) | 56,723 (34%) | 55,233 (39%) | 67,956 (52%) |
| UFO | 15,110 (14%) | 27,188 (15%) | 17,787 (11%) | 3,985 (3%) | 3,415 (3%) |
| Pearson's Chi-squared test: | | | | | |
| $\chi2$ = 89,078 | | df = 16 | | p-value < 2.2e-16 | |

The increase in PPA quoting behavior from 2015 to 2016 provides evidence contrary to H1 and suggests that the financing firm and associated installation companies differ from other large-scale solar PV providers over the same time frame. One reason for this might be that the installation companies that partner with this firm do not resemble the vertically integrated installers that are driving the strategic shift from TPO to direct ownership. While vertically integrated installers are providing decreased TPO services in an effort to reduce overhead and customer acquisition costs, smaller installers may see an ongoing opportunity to attract customers with TPO services.

Notably, lease prevalence drops off from 2012 to 2016 as PPA prevalence rises, suggesting that there is an incentive for the financing firm or installers to favor PPAs over leases. Leases, like PPAs, can help customers to overcome barriers to adoption such as high upfront cost and aversion to risk associated with adoption (Rai and Sigrin 2013; Rai et al. 2016), and leases have been shown to reduce overall costs for customers compared to PPAs (Davidson et al. 2015). While customer preferences for leases versus PPAs are not known within this dataset, it is unlikely that this supply-side imbalance can be interpreted fully as an installer response to demand-side preference for PPAs.

*4.2: Financing Product Type and Market Maturity*

To address our second research question and H2, we developed a methodology for determining whether quotes in the financier dataset occurred in mature or nascent markets. TTS was used to classify the maturity of markets, since it provides the most comprehensive comparison of solar markets across the United States. We adopted the approach of using county boundaries as a PV market proxy (Gillingham et al. 2016; Nemet et al. 2017), and we defined the maturity of county-level markets each year from 2012 to 2016. We then assigned these county-year level market maturity classifications from TTS to the quote-level financier dataset, so that each quote in the financier dataset was flagged with a market maturity classification.

To prepare the TTS dataset for analysis, we excluded installations occurring in counties with less than two active installers in any year from 2000 to 2016. Prior to applying this minimum installer criterion, the sample of nascent markets included many instances in which only one installation occurred over the study timeframe. To restrict the market sample to regions with more robust installation activity, we defined markets as county-year instances in which there was competition between at least two installers. Of 48,848 county-year instances present in TTS, 476 involve only one active installer and were removed from the dataset.

We next assigned each county-year observation a market maturity status of mature (M), nascent (N), or other (O). These classifications were defined using five metrics based on TTS data, including 1) entry year, calculated as the first year since 2000 when at least 5 installations occurred in a given county, 2) installations per county per year, 3) cumulative installations per county from 2000 until the year of analysis, 4) unique installers per county per year, and 5) cumulative unique installers from 2000 until the year of analysis. All metrics except entry year were normalized by the number of household units per county per year using Census data.

For each year from 2012 to 2016, counties received 1 "nascent point" for each instance that they fell into the bottom 30th percentile of a metric. For example, recent entry year values and low cumulative installer values correspond with market nascence. Each county-year instance could receive a maximum of 5 nascent points by falling in the bottom 30$^{th}$ percentile of all five metrics. Likewise, counties, per year, received 1 “mature point” for each instance that they fell into the 70th through 100th percentile of a metric, up to a maximum of 5 mature points. County-year instances with 5 nascent points were classified as nascent; county-year instances with 5 mature points were classified as mature; and all remaining county-year observations were classified as “other.” This methodology identified sets of mature and nascent markets that, in each year, are separated in terms of market longevity, installer overlap, and the penetration of solar installations among residential households in the county. Note that this method allows for counties to fall in and out of the mature and nascent market samples over time. For example, if County A receives 5 nascent points in 2013 but only 4 nascent points in 2014, then County A is classified as nascent in 2013 and “other” in 2014.

Table 2 outlines the mature and nascent markets identified in each state from 2012 through 2016. All mature markets were identified in California, with the addition of one county in New Jersey in 2012. Nascent markets were identified in a broader geography, with most occurrences in New York, Pennsylvania, and Wisconsin. Table 3 summarizes the mean values of each market maturity metric in mature and nascent markets. These results reveal that mature markets identified through this classification methodology are substantially different from nascent markets, allowing for these two market classes to be compared as distinct settings. The nascent markets identified have robust activity in terms of yearly installations and unique installers, with a minimum of 45 yearly installations and 8.5 unique installers in 2014.

***Table 2:*** *Summary of the count of mature and nascent markets identified per state each year from 2012 to 2016. The use of percentile cutoffs for mature and nascent market identification allows counties to fall in and out of the market samples over time. For example, while New Jersey was above the 70$^{th}$ percentile in all five market maturity metrics in 2012, by 2013 it fell below the 70$^{th}$ percentile in at least one metric and so dropped out of the mature market sample.*

| Mature and Nascent Markets by State and Year | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2012 | | 2013 | | 2014 | | 2015 | | 2016 | |
| | M | N | M | N | M | N | M | N | M | N |
| CA | 14 | | 16 | | 23 | | 20 | | 19 | |
| DE | | 1 | | | | | | | | 1 |
| IL | | 1 | | 5 | | 7 | | 4 | | 2 |
| MD | | 2 | | 3 | | 2 | | 2 | | 2 |
| MN | | | | | | 4 | | 6 | | 5 |
| NH | | 3 | | 3 | | 1 | | 1 | | 2 |
| NJ | 1 | | | | | | | | | |
| NM | | 1 | | | | 2 | | 2 | | 2 |
| NV | | | | 1 | | | | | | |
| NY | | 10 | | 10 | | 8 | | 7 | | 7 |
| OR | | 1 | | 1 | | 1 | | 1 | | 4 |
| PA | | 16 | | 14 | | 2 | | 1 | | 1 |
| WI | | 7 | | 9 | | 9 | | 11 | | |
| Total | 15 | 42 | 16 | 46 | 23 | 36 | 20 | 35 | 19 | 26 |

***Table 3**: Summary of the mean values of five metrics used to classify mature and nascent markets in TTS: 1) entry year, 2) yearly installations, 3) cumulative installations beginning in 2000, 4) yearly unique installers, and 5) cumulative unique installers beginning in 2000. Here, mean values are reported prior to normalization by household units. These results reveal a divide between mature and nascent markets in terms of longevity, solar penetration, and installer overlap, and also that the methods used identify nascent markets with robust solar PV activity.*

| Market Maturity Metrics: Average by Year and Market Class | | | | | | |
|---|---|---|---|---|---|---|
| | | 2012 | 2013 | 2014 | 2015 | 2016 |
| *Entry Year* | | | | | | |
| | Mature | 2002 | 2002 | 2002 | 2002 | 2002 |
| | Nascent | 2010 | 2010 | 2011 | 2011 | 2011 |
| *Yearly Installations* | | | | | | |
| | Mature | 332.4 | 735.2 | 1292 | 2201 | 2359 |
| | Nascent | 76.16 | 51.04 | 45.01 | 96.73 | 279.1 |
| *Cumulative Installations* | | | | | | |
| | Mature | 1711 | 2641 | 3810 | 6248 | 9240 |
| | Nascent | 174.6 | 150.7 | 116.5 | 211.6 | 554.3 |
| *Yearly Unique Installers* | | | | | | |
| | Mature | 58.57 | 80.04 | 94.53 | 136.9 | 130.3 |
| | Nascent | 16.93 | 10.58 | 8.449 | 11.93 | 13.68 |
| *Cumulative unique installers* | | | | | | |
| | Mature | 382.3 | 483.8 | 514.4 | 669.2 | 812.7 |
| | Nascent | 44.99 | 44.74 | 35.15 | 48.94 | 71.22 |

Once a market maturity classification had been assigned to each county-year instance in TTS, we joined these classifications to the quote-level dataset provided by the solar financing firm based on county and year. The result of this was a database including, among many variables, the financing product type, year, installer, and market maturity classification associated with over 760,000 quotes. Throughout the analysis described in this section as well as in section 4.3, we exclude all markets identified as "other," leaving a sample of 127,315 quotes occurring in mature or nascent markets.

The year-over-year prevalence of each financing product type in mature versus nascent markets, summarized in Table 4, suggests that financing product trends do differ in the two market classes. In mature markets, cash financing was the most common product across the study period and showed an upward trend. PPAs showed a rapid rise in 2013 and then gradually increased through 2016. Lease, loan, and UFO financing had a year-over-year decline. In nascent markets, cash offers started off as the only financing product in 2012 and then, in contrast to mature markets, showed a general downward trend. Leases appeared in 2013, and in 2014 there were more leases in nascent markets than in mature markets. In 2015 nascent markets, leases declined as UFOs and PPAs rose in prominence. PPAs dramatically rose in 2016, accounting for nearly 80% of all financing offers that year and replacing cash offers as the most common financing product.

***Table 4:*** *Count of five financing product types in mature and nascent markets. These raw counts of financing products from 2012 to 2016 suggest differences in financing trends in the two market classes. In mature markets, cash offers were consistently the most prominent financing product and rose in prevalence over time. PPAs showed a rapid increase in 2013 and then a slow upward trend through 2016. Leases, loans, and UFOs downwardly trended. In nascent markets, cash offers declined over time. Leases were the first financing product to rise in prominence, followed by UFOs and then leases in 2014-2015. PPAs showed a dramatic increase in 2016, replacing cash offers as the most common financing product.*

| **Financing Product Types by Year and Market Class** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 2012 | 2013 | 2014 | 2015 | 2016 | Total |
| Cash | | | | | | | |
| | M | 5410 | 11105 | 21262 | 19051 | 13993 | 70821 |
| | N | 974 | 771 | 574 | 423 | 230 | 2972 |
| Lease | | | | | | | |
| | M | 2671 | 72 | 200 | 1276 | 30 | 4249 |
| | N | 0 | 50 | 263 | 51 | 0 | 364 |
| Loan | | | | | | | |
| | M | 874 | 1253 | 906 | 259 | 50 | 3342 |
| | N | 1 | 10 | 2 | 0 | 4 | 17 |
| PPA | | | | | | | |
| | M | 1080 | 8423 | 8571 | 8234 | 10680 | 36988 |
| | N | 0 | 1 | 0 | 19 | 968 | 988 |
| UFO | | | | | | | |
| | M | 1331 | 2867 | 1917 | 565 | 826 | 7506 |
| | N | 0 | 0 | 6 | 47 | 15 | 68 |
| Total | | 12341 | 24552 | 33701 | 29925 | 26796 | 127315 |

For remaining analyses, cash offers were dropped from the dataset to allow focus on supply-side trends in non-cash solar financing products. Figure 2 depicts the relative proportions of non-cash financing products in mature versus nascent markets over time. Pearson's chi-squared tests reveal that financing product is not independent of market classification ($\chi^2$ = 662.05, df = 4, p-value < 2.2e-16), suggesting the need for further exploration of the relationship between financing product type and market classification in regression modeling (Table 5).

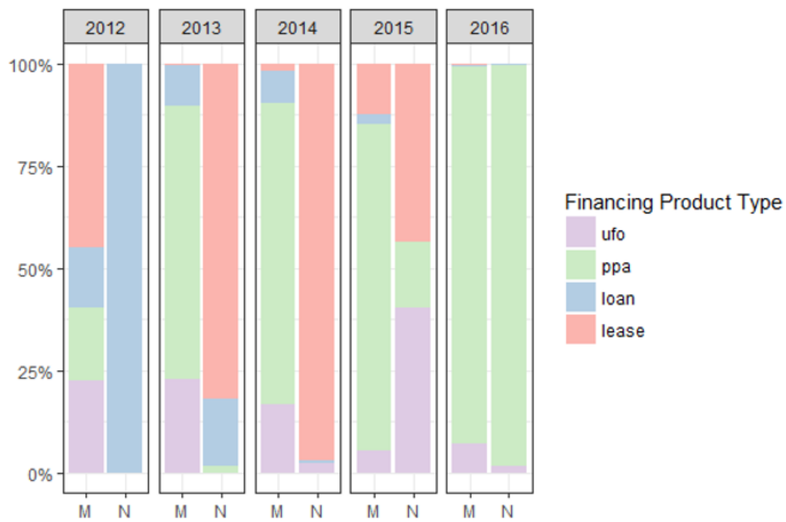


***Figure 2:*** *Relative proportion of non-cash financing product types in mature and nascent markets over time*

***Table 5:*** *Pearson's Chi-squared tests reveal a significant relationship between financing product type and time as well as financing product type and market maturity classification, suggesting that both time and market classification should be explored as independent variables explaining financing product type.*

| Financing Product Type and Market Class | | |
|---|---|---|
| | M | N |
| cash | 70821 | 2972 |
| lease | 4249 | 364 |
| loan | 3342 | 17 |
| ppa | 36988 | 988 |
| ufo | 7506 | 68 |
| Pearson's Chi-squared test: | | |
| χ2 = 662.05 | df = 4 | p-value < 2.2e-16 |

*4.3: Multinomial Logistic Regression Analysis of Financing Product Likelihood*

In this section, we describe three multinomial logistic regression models used to assess the influence of year and market maturity on the likelihood of the offer of each non-cash financing product type. This approach is appropriate with a categorical dependent variable that takes more than two levels: PPA, lease, UFO, or loan. Each model's output disambiguates the relative impact of predictor variables on the log odds of each financing product type compared to a reference financing product type within a given year and market maturity class. In these models, the offer of a loan is the reference financing type since it is the only non-TPO option. Additionally, setting loan as the reference type reduces the *empty cell effect,* which occurs when there are 0 instances of a financing product in a given year and market type. This is particularly problematic when the empty cell is the denominator of the dependent variable (see Equation 1).

The model used calculates the log odds of lease, PPA, and UFO quotes compared to the reference group, loan quotes in 2012 mature markets, as a function of market maturity classification, fixed effects by year, interaction between year and market maturity, and fixed effects by state, per the following equation:

***Equation 1***

$$ln\left(\frac{\pi(offer=f)_{it}}{\pi(offer=base)_{it}}\right) = \alpha + \beta M_{it} + \gamma Y_t + \delta M_{it} Y_t + \varphi S_i$$

where the dependent variable is the log ratio of $\pi(offer = f)_{it}$, the probability that a given offer is a particular financing product type, *f*, in state *i* and time *t,* and $\pi(offer = base)_{it}$, the probability of that an offer is in the reference group comprised of loan offers in mature markets in 2012. Among predictor variables, α is the coefficient for the intercept term, $\beta$ is the coefficient for $M_{it}$, , market maturity classification in state *i* and time *t*, $\gamma$ is the coefficient for $Y_t$, fixed effect by year, $\delta$ is the coefficient for the interaction of $M_{it}$ and $Y_t$, and $\varphi$ is the coefficient for $S_i$, fixed effects by state. Model 1 forces a coefficient of 0 for state fixed effects and year-nascence interaction, and so calculates the log odds of each financing product type compared to the reference group as a function of the intercept term, market maturity classification, and unobserved heterogeneity attributable to year. Model 2 builds on Model 1, adding fixed effects by state for additional control of heterogeneity due to state. The decrease in AIC in Model 2 suggests that state fixed effects improve the model. Finally, Model 3 adds year-nascence interaction and produces the lowest AIC, making Model 3 the preferred model for predicting the log odds of each financing product type.

Table 6 summarizes the coefficients for each predictor and dummy variable in Models 1, 2, and 3. The intercept coefficients indicate the multinomial logit estimates of each financing product type compared to loans when all predictor variables are held to 0. In Model 3, a coefficient of 1.117 on lease suggests that the logit for an outcome of lease relative to loan is 1.117. Coefficients in the nascence row indicate the multinomial logit adjustment when a bid occurs in a nascent market, given that all other variables are held constant. For example, when a market is classified as nascent, the log odds of a lease compared to loan drop by -60.722. Coefficients for year fixed effects and year-nascence interaction are interpreted similarly. To assess the overall log odds adjustment for a lease in a nascent market in 2016, the lease coefficients for the intercept, nascence, 2016, and nascence x 2016 terms are added. The resulting coefficient value suggests that a PPA in a 2016 nascent market is approximately 240 times ($e^{0.212-8.361+5.152+8.483} = e^{5.486}$=241.281) as probable as a loan in the same context.

Odds ratios of each financing type per year and market class were calculated by exponentiating the sum of coefficients relevant for each year, market class, and financing product type combination (Table 7). For example, mature markets have a coefficient of 0 for the nascence and nascence-year terms, and the odds ratios are found by exponentiation of the sum of coefficients on the intercept and year. These odds ratios indicate the “risk” that quotes fall into the comparison groups, e.g. leases, PPA, or UFO, given all predictor variables used in Model 3. An odds ratio greater than 1 indicates that the comparison outcome is more likely in a given year and market context than loans, whereas an odds ratio lesser than 1 indicates that a loan is more likely. Additionally, the odds ratios of leases, PPAs, and UFOs can be compared to identify the relative odds of each financing type. For example in 2012 mature markets, leases (odds ratio = 3.056) were more likely than UFOs (1.523), which were more likely than PPAs (1.236). By contrast, these odds ratios flipped in 2016, in which leases were the least likely (0.600), followed by UFOs (16.516) and then PPAs (213.281). The odds ratios are normalized and depicted as predicted probabilities in Figure 3.

***Table 6.*** *Results from a series of multinomial logistic regression models testing the log odds that suppliers bid leases, PPAs, or UFOs compared to loans given predictor variables, market maturity classification and year. The reference group is comprised of quotes with loan financing offers in mature markets in 2012. The coefficients in the baseline row provide the log odds of bids with loan, PPA, and UFO financing compared to leases in mature markets in 2012. A positive coefficient in this row indicates that a financing product type is more likely than a loan within this year and market type. The second row, nascence, indicates the adjustment that classification as a nascent market contributes to the log odds of loans, PPA, and UFO quotes compared to loans in the reference group. The coefficients of fixed effect by year can be interpreted as log-odds adjustments to the baseline and nascence coefficients to account for the effect of year. Finally, Model 3 includes coefficients explaining how year x nascence interaction adjusts the log odds of bids with lease, PPA, or UFO financing compared to loans in the baseline group.*

| **Log-Odd Coefficients** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | Model 2 | | | Model 3 | | |
| | Lease | PPA | UFO | Lease | PPA | UFO | Lease | PPA | UFO |
| (Intercept) | 1.116 | 0.210 | 0.419 | 1.116 | 0.135 | 0.407 | 1.117 | 0.212 | 0.421 |
| | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| | *(0.039)* | *(0.045)* | *(0.044)* | *(0.039)* | *(0.046)* | *(0.044)* | *(0.039)* | *(0.045)* | *(0.044)* |
| Nascence | 4.506 | -0.223 | -0.470 | -2.427 | -7.525 | -4.916 | -60.722 | -8.361 | -31.169 |
| | *** | | | *** | *** | *** | *** | *** | *** |
| | *(0.262)* | *(0.257)* | *(0.280)* | *(0.258)* | *(0.291)* | *(0.308)* | *(0.250)* | *(0.340)* | *(0.304)* |
| 2013 | -3.714 | 1.688 | 0.402 | -3.728 | 1.764 | 0.414 | -3.974 | 1.694 | 0.407 |
| | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| | *(0.108)* | *(0.055)* | *(0.055)* | *(0.110)* | *(0.055)* | *(0.055)* | *(0.127)* | *(0.055)* | *(0.055)* |
| 2014 | -2.338 | 2.036 | 0.334 | -2.349 | 2.110 | 0.343 | -2.628 | 2.035 | 0.329 |
| | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| | *(0.079)* | *(0.057)* | *(0.059)* | *(0.079)* | *(0.058)* | *(0.059)* | *(0.087)* | *(0.057)* | *(0.059)* |
| 2015 | 0.433 | 3.251 | 0.441 | 0.437 | 3.328 | 0.453 | 0.478 | 3.248 | 0.359 |
| | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| | *(0.079)* | *(0.078)* | *(0.086)* | *(0.079)* | *(0.078)* | *(0.086)* | *(0.079)* | *(0.078)* | *(0.087)* |
| 2016 | -3.953 | 5.184 | 2.364 | -3.998 | 5.288 | 2.407 | -1.628 | 5.152 | 2.384 |
| | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| | *(0.258)* | *(0.146)* | *(0.149)* | *(0.265)* | *(0.150)* | *(0.153)* | *(0.234)* | *(0.149)* | *(0.152)* |
| Nascence x 2013 | | | | | | | 65.188 | 4.153 | -17.040 |
| | | | | | | | *** | *** | *** |
| | | | | | | | *(0.342)* | *(0.774)* | *(0.000)* |
| Nascence x 2014 | | | | | | | 67.113 | -6.850 | 31.519 |
| | | | | | | | *** | *** | *** |
| | | | | | | | *(0.511)* | *(0.000)* | *(0.602)* |
| Nascence x 2015 | | | | | | | 89.838 | 34.625 | 61.018 |
| | | | | | | | *** | *** | *** |
| | | | | | | | *(0.177)* | *(0.249)* | *(0.180)* |
| Nascence x 2016 | | | | | | | 31.163 | 8.483 | 29.683 |
| | | | | | | | *** | *** | *** |
| | | | | | | | *(0.000)* | *(0.470)* | *(0.477)* |
| State fixed effect? | no | | | yes | | | yes | | |
| Residual Deviance | 78185.05 | | | 77854.39 | | | 77337.63 | | |
| AIC | 78221.05 | | | 77926.39 | | | 77397.63 | | |

*Note: standard error in parentheses*

Significance stars: *p<0.1; **p<0.05; ***p<0.001

***Table 7:*** *Model 3 odds ratios, which are calculated by exponentiating the sum of coefficients for the intercept, nascence, year fixed effects, and year x nascence interaction effects. Here, a value of 5.0 for nascent markets in 2013 suggests that the relative risk of leases in 2013 nascent markets is 5 times greater than loans in 2013 nascent markets.*

| Odds Ratios of Lease, PPA, and UFO Quotes Compared to Loans | | | | | | |
|---|---|---|---|---|---|---|
| | Lease | | PPA | | UFO | |
| | M | N | M | N | M | N |
| 2012 | 3.056133 | 1.301E-26 | 1.236 | 2.888E-04 | 1.523 | 4.428E-14 |
| 2013 | 0.057454 | 5.000 | 6.722 | 0.100 | 2.288 | 2.645E-21 |
| 2014 | 0.220729 | 131.735 | 9.460 | 2.343E-06 | 2.116 | 3.003 |
| 2015 | 4.927227 | 2.175E+13 | 31.794 | 8.104E+12 | 2.182 | 2.005E+13 |
| 2016 | 0.600 | 8.724E-14 | 213.557 | 241.281 | 16.516 | 3.737 |

The results from Model 3 provide evidence that financing product trends differ in mature and nascent markets and that the introduction of TPO financing products in nascent markets tends to lag behind mature markets. Additionally, with the exception of PPAs, the results partially confirm H2, indicating that TPO options continue to be offered in nascent markets as they decline in mature markets. In 2012, mature markets had a diverse mix of loans, leases, PPAs, and UFOs, with loans at about 50% predicted probability. In that year, non-cash financing was absent from nascent markets in all forms with the exception of one loan (Table 4). Over the next year, PPAs rose rapidly in mature markets but not at all in nascent markets, and leases declined in mature markets as they rose to be the first non-cash financing product in nascent markets. From 2013 to 2014, mature markets saw a continued gradual increase of PPA prevalence as loans, leases, and UFOs declined. In contrast, leases rose to about 100% predicted probability in nascent markets as all other non-cash financing products remained flat at 0. As PPAs continued to rise in mature markets over the next year, nascent markets saw a sudden decline of leases as UFOs rose to prominence and PPAs appeared. PPAs had a sudden rise in nascent markets over the next year, so that by 2016 nearly all non-cash offers in mature and nascent markets involved PPA financing.

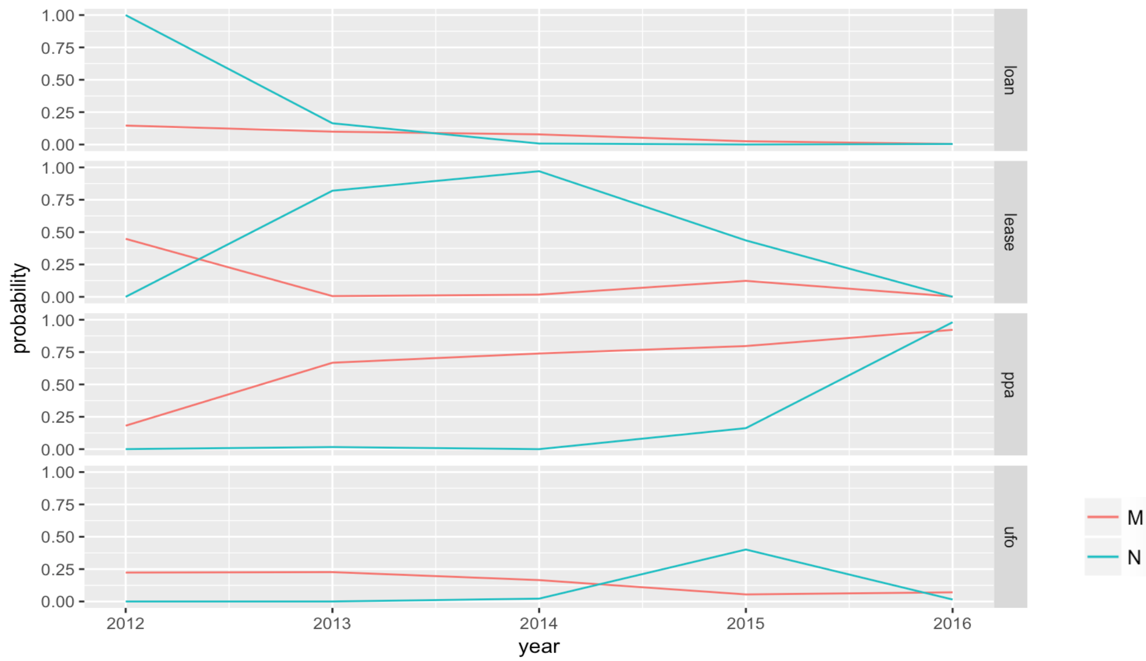


***Figure 3:*** *predicted probabilities of each non-cash financing options over time in mature and nascent markets. Trends in nascent market TPO financing appear to lag behind mature market trends, with both market types showing an eventual supply-side preference for PPAs. This figure presents the baseline probability of each financing product offer with the addition of including fixed effects by state. Future models that incorporate additional predictors such as fixed effects by installer may lead to predicted probabilities that vary greatly compared to the baseline probabilities.*

These findings suggest that installers operating with the financing firm in mature markets identified a preference for PPA by 2013 and over time decreased offers of all other non-cash financing products. In contrast, installers in nascent markets preferred leases in 2013 and 2014, UFOs in 2015, and finally PPAs in 2016. This dataset does not provide insight into the patterns of lease, loan, and UFO offers prior to 2012, so it is not known if the order of introduction of each financing product in mature markets resembled the trends found here in nascent markets. Interestingly, leases were the most prominent financing type in mature markets in 2012, and over the next two years leases became the most common financing product in nascent markets. UFOs were the second-most prominent in mature markets in 2012, and UFOs were the second financing product to rise in prominence in nascent markets. PPAs rose to prominence in mature markets in 2013, and 3 years later nascent markets followed.

## Discussion

In this paper, we use a proprietary dataset provided by a national-scale solar PV financing firm to explore supply-side trends in the prevalence of solar loans, leases, PPAs, and upfront financing offers in mature and nascent markets. By performing this analysis at the level of installer quotes to customers, we are able to describe trends in the *availability* of various financing product types over time and in different contexts. Our first finding is that the installers present in this dataset increased PPA offers from 2015 to 2016, so that by 2016 PPAs were the only non-cash financing product available to customers in both nascent and mature markets. This trend opposes the broader residential PV market, which saw a decline of TPO in 2016 (Litvak 2017; Perea et al. 2017). Secondly, we found that installers who use this firm's financing services in nascent markets tend to offer TPO options one or more years later than installers in mature markets. While mature markets had a diverse spread of TPO products in 2012, nascent markets did not have access to leases until 2013 and UFOs and PPAs until 2015. The sudden rise in PPAs that occurred in mature markets in 2013 did not occur in nascent markets until 2016.

The most critical next step for the analysis presented in this paper is to test the sensitivity of results to alternate definitions of market maturity. For example, new percentile cutoffs or new metrics could be applied to classify maturity and nascence. Additionally, the analyses could be repeated with an alternative market definition, such as one that delineates markets based on installer overlap (O'Shaughnessy et al. 2016).

The installers in this dataset differ from leading national installers in that they use an external financial services firm to offer TPO options rather than offering TPO in-house. In general, only national-scale installation firms have been able to monetize the tax incentives of providing TPO services (MIT 2015), and so TPO trends have been primarily driven by large vertically integrated installers (O'Shaughnessy 2018). As vertically integrated firms move toward a direct ownership strategy in their efforts to decrease customer acquisition and other soft costs, mid-size and smaller firms might have incentive to continue offering TPO services if those services help to attract new customers. This might partially explain why the installers in this dataset increased PPA offers in 2016 even as the broader market began to move away from PPAs. Future research could explore this hypothesis by characterizing installers in mature and nascent markets and then exploring how installer size and geographic reach predict the likelihood that suppliers offer each financing product type in different market settings over time.

This analysis does not address *why* nascent-market installers lag behind mature-market installers in offering TPO quotes to customers. On the one hand, if installers are responding to customer demand for financing products, this could suggest that demand for TPO products is low when those products are new and unfamiliar and then rises as those products become more familiar. On the other hand, it is possible that the lag in TPO quoting behavior is explained on the supply side, e.g. that nascent-market installers are not aware of TPO financing services or do not see a benefit of offering them to customers. An additional direction for future solar diffusion research would attempt to explain interactions between supply-side and demand-side trends in solar financing.

**Conclusion**

This paper contributes to solar diffusion literature by providing a supply-side analysis of residential solar PV financing products offered over time to customers in different market settings. Descriptive analysis and multinomial logistic regression modeling of a proprietary dataset of solar financing quotes reveal that there are significant differences in the likelihood that PPAs, leases, UFOs, and loans are offered to customers in mature and nascent markets. The methodologies presented here can be built upon in future studies to determine whether and how supply-side trends in solar financing in emerging markets may constrain and influence customer adoption.

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